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Fuzzy clustering of human locomotor motion

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1. Introduction

Acquisition of behavioural skills of a human operator and recreating them in an intelligent autonomous system has been a critical but rather challenging step in the development of complex intelligent autonomous systems. A systematic and generic method for realising this process will greatly simplify the development, commissioning and maintenance of autonomous systems.

A human operator automatically employs tacit skills to perform a dynamic real time task. Application of conventional knowledge acquisition systems is not sufficient to acquire the employed skills as the operator is typically unable to provide an accurate and complete description of the employed skills and their sequence [1].

There have been a number of attempts to overcome some of the shortcomings of "teaching by guiding" approach. Summers and Grossman[2] embedded a collection of the sensory information and interaction with the operator in the task instruction procedure. Asada and Assari[3] used neural networks to extract the control rules to perform a particular assembly motion from the position and force data generated during operation of a human operator. Due to unintentional and inconsistent motion commands generated by the operator during demonstration, direct training has proved difficult. Sator and Hirai[4] integrated direct teaching with task level languages through master-slave manipulators.

In addition to self-discovery, learning of skills in humans generally takes place through training by an instructor[5] in the *psychomotor* domain, where 'motor' is an observable movement response to a stimulus[6]. According to Smith and Smith[7], there are three types of movements. The first is the *postural* movement which regulates body positioning. The second is *locomotor* movements, which translate and rotate a body, and the third category includes *manipulative* movements. In this work the focus is on postural and locomotor movements. The perception of such movements is the primary purpose of the work reported in this paper. In long term, such perception will be used by a humanoid robot to mimic human psychomotor behaviour.

In this work, a fuzzy clustering method is deployed to identify different movements of human hand. The motion of the hand is measured by a dual-axis accelerometer and a gyroscope mounted on it. The gyroscope locates the position and configuration of the body, and the accelerometers measure the kinematics parameters of the movement. The covariance and the mean of the data produced by the sensors are used as features in the clustering process. The approach is based Fuzzy-C-Mean algorithm clustering method[8] and employs a Feed-Forward Neural Network (FFNN) to estimate the characteristics of each cluster.

In the course of the full paper, the work conducted so far and the results obtained will be reported. The experimental rig will be initially described and the typical data samples produced by the sensors are provided. The feature extraction applied to the data will be described and fuzzy clustering algorithm applied to derive the fuzzy membership values will be explained. Finally the classification algorithm developed will be described and validated.

2. Experimental Set up

The study is currently focused on study and perception of different types of hand movements. The dual axis accelerometer and the gyroscope are mounted to the hand as shown in Figure 1. It is possible to identify 6 different hand motion primitives as illustrated in Figure 2: Arm moving up-down; arm moving to the right and left; wrist moving in 2 directions with two different orientations of human arm. This will create four motion primitives for the wrist. The aim of this study is to recognise these four different wrist movements.

Figure 1 – Mounting of the sensors on hand

Figure 2 – Movements of the hand

The accelerometer, Analog Devices ADXL203 is a high precision, low power, complete single and dual axis accelerometer with signal conditioned voltage outputs, all on a single monolithic IC. The ADXL203 measures acceleration with a full-scale range of ±1.7 *g*. The ADXL203 can measure both dynamic acceleration (e.g., vibration) and static acceleration (e.g., gravity).

The gyroscope, Analog Devices ADXRS300 is a complete angular rate sensor (gyroscope). The output signal, RATEOUT (1B, 2A), is a voltage proportional to angular rate about the axis normal to the top surface of the package. A single external resistor can be used to lower the scale factor. An external capacitor is used to set the bandwidth.

The data produced by the sensors are fed into a PMD-1208LS data acquisition system. This is a USB low-speed device usually used for data acquisition and control applications. The device has eight analog inputs, two 10-bit analog outputs, 16 digital I/O connections and one 32-bit external event counter. The device is powered by the +5 volt USB supply and does not require any external power is required. An example of the four wrist motion primitives recorded by the experimental rig is illustrated in Figure 3.

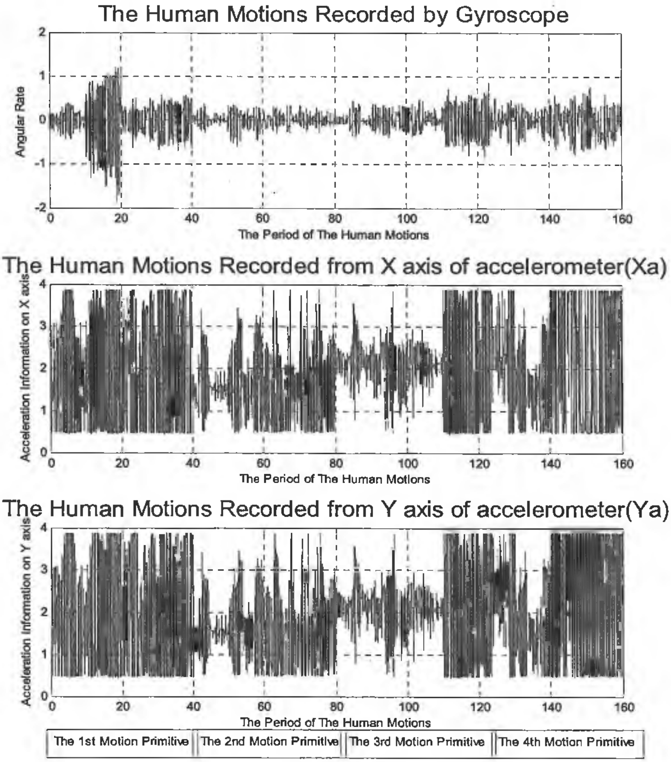

Figure 3 – Data produced by the sensors

3. The Fuzzy Clustering Algorithm

It is a big challenge to develop a nonlinear function to describe the relationship between the 3D sensory inputs and the 6 different motion primitives. Although developing relevant mathematical model can also separate the recorded data into different motion primitives, the model must lose the generality to describe other different motion primitives. Therefore, it is desired to develop a generic and efficient approach on the basis of fuzzy clustering algorithm which is proposed to categorize the acquired data into several groups with a membership degree for each group.

The fuzzy clustering algorithm calculates the expected membership value u_{ij} for motion data i in primitive j, by minimizing the objective function (1)[9]..

$$J(X,U,C)=\sum_{i=1}^{c} J_i=\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \quad (1)$$

In which, u_{ij} is the degree of membership for each object; $u \in [0,1]$ and $\sum_{i=1}^{c} u_{ij}=1, \forall j=1,\ldots,n$.

Where X is the data set: $X=(x_j \mid j=1,\ldots,n)$

C is the cluster centres matrix;

d_{ij} is $d_{ij}=\sqrt{(x_j-c_i)^T A(x_j-c_i)}$

A is any symmetric positive definite matrix.

$m \in [1,\infty]$ is the degree of fuzziness.

Without considering the characteristics of the nonlinear system, the symmetric positive definite matrix A could be set as an identity matrix. However, since the clustering results is based on the set up as shown in figure 1, it is necessary to define a particular matrix A to represent the characteristics of the system. Matrix A is calculated based on the covariance matrix F (Equation (2)). Matrix F, in turn is derived from the measured data according to equation 3, using Gustafson-Kessel algorithm[10].

$$A_i = \det(F_i)^{\frac{1}{n}} F_i^{-1} \quad (2)$$

$$F_i = \frac{\sum_{j=1}^{n} (u_{ij})^m (x_j - c_i)^T (x_j - c_i)}{\sum_{j=1}^{n} (u_{ij})^m} \quad (3)$$

As illustrated by equation (3), the covariance matrix F is a symmetric matrix which describes the distribution of data in a multiple-dimensional space with a fuzzy degree assigned to each group. Given the eigenvector and eigenvalue of F, it is supposed that all the clusters derived from F can be presented as several hyper-ellipsoids. The functions describing these hyper-ellipsoids must be continuous and nonlinear in a finite domain.

According to Schalkoff[11], if a function is continuous in a finite domain, the three-layer-FFNN (Feed-Forward Neural Network) has the ability to approximate it with an arbitrary precision. Therefore, the FFNN is applied in this work to achieve clustering by finding the optimal value of u_{ij}. If the membership degrees of the training data are haphazard so that the function to describe them is not continuous, the errors of FFNN would be bigger than the tolerance values. Fine adjustment of the membership values should be applied to all the training data until the errors of FFNN is within the tolerance level. It is proposed that the patterns constructed by the covariance matrix F could be applied to perform the pattern recognition process.

4. Application of the Approach

In building the pattern recognition system, a number of features have been derived from the data obtained from the sensors. This includes the covariance of data obtained from the accelerometers and gyroscope, the mean of those data, and the covariance of the positions of the hand obtained from the gyroscope signal. A typical covariance of the position of the hand is illustrated in Figure 4.

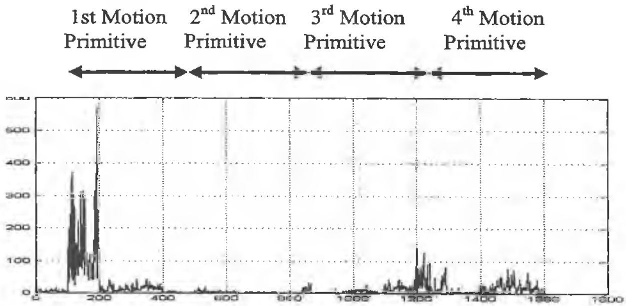

Figure 4 - Covariance of the Positions of the hand

In addition, the velocity of the hand in two directions and the rotation angle of the hand are obtained through the second integral of acceleration and the first integral of gyroscope signal respectively. The feature selection is carried out over a specific length of data determined according to the clustering requirements.

The fuzzy classification algorithm was applied to the data obtained from the sensors and the covariance coefficient matrix for each motion primitive was calculated using equation (3). The results obtained are as follows:

Motion Primitive 1: $F_1 = \begin{bmatrix} 0.015594 & 0.0085499 & -0.0010664 \\ 0.0085499 & 0.045897 & -0.0015266 \\ -0.0010644 & -0.0015266 & 0.0083993 \end{bmatrix}$

Motion Primitive 2: $F_2 = \begin{bmatrix} 0.057076 & 0.0011036 & 0.0061003 \\ 0.0011036 & 0.011573 & -0.00069221 \\ 0.0061003 & -0.00069221 & 0.0057986 \end{bmatrix}$

Motion Primitive 3: $F_3 = \begin{bmatrix} 0.06517 & -0.00067402 & -0.0054919 \\ -0.00067402 & 0.017014 & 0.0035682 \\ -0.0054919 & 0.0035682 & 0.012819 \end{bmatrix}$

$$\text{Motion Primitive 4: } F_4 = \begin{bmatrix} 0.016214 & 0.00041404 & 0.0046662 \\ 0.00041404 & 0.056651 & 0.0024119 \\ 0.0046662 & 0.0024119 & 0.020522 \end{bmatrix}$$

The patterns can be represented as a series of 3 dimensional ellipsoids which are shown as in figure 5

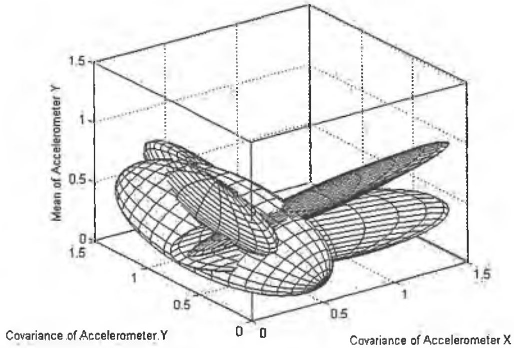

Figure 5 – The Patterns Representing the Wrist Shaking Primitives.

The algorithm was further validated by applying it to a series of human wrist motions recorded by the data acquisition system. As illustrated in Figure 5, the sequence of these motion primitives is identified as motion primitives 3, 4, 5 and 6. Short periods of movements in these motion primitives are removed by replacing them with the second biggest values of the primitives as shown in Figure 6.

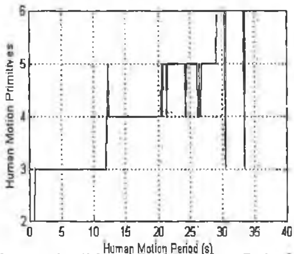

Figure 6 – Identified Motion Primitives

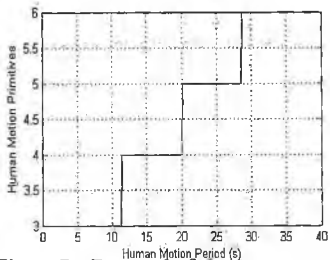

Figure 7 – Removal of short movements

5. Conclusions

Fuzzy clustering based on the characteristics of a system is an effective approach to achieve Rough Data Model to generate robot imitation by observing human demonstration. It is, however, quite challenging to describe the characteristics of a system though some parameters as the human motion is complicated and fuzzy. In this work, the human hand motion is represented by a number of motion primitives. An approach based fuzzy clustering algorithm has been developed to describe such representations. The algorithm has been validated through some experimental works. A large number of data pairs have been divided into two parts of testing data and training data. The results indicate that the approach can identify different hand motion primitives.

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